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Utilizing Transfer Learning For Image Classification In Diabetic Retinopathy Images

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Abstract:
Until now, Computer-Aided Diagnosis (CAD) systems have played a crucial role in the early detection of many cancer cases. Despite various approaches proposed in the field of medical image processing to tackle this issue, their results have been found lacking. Moreover, the integration of AI into Diabetic Retinopathy (DR) images remains limited in hospital settings. The classification of DR images poses a greater difficulty compared to other image types. In this research, we utilize transfer learning, specifically leveraging the Inception V3 model, to classify DR images. We make use of the pre-trained weights of the Inception V3 model obtained from the ImageNet dataset and perform fine-tuning on our own dataset. Our results exhibit a higher accuracy when compared to alternative methods proposed in the literature.

Keywords —**Medical image, CAD, DR images, Transfer Learning.**

I. INTRODUCTION

In the United States, around one in eight women is impacted by breast cancer, leading to approximately 40,000 annual deaths related to cancer and involving 1.3 million individuals undergoing cancer treatment. The incidence of breast cancer in Asia is rising by 1.7% per year. Our study focuses on utilizing Digital Radiography (DR) images, particularly for lung cancer detection, employing the Inception V3 model due to its efficacy. DR images outperform Computed Radiography (CR) images, primarily due to their higher resolution.

The past decade has witnessed a surge in image processing technology within the medical field, significantly contributing to the early detection of diseases. Image processing encompasses various domains such as classification, segmentation, enhancement, and assessment. Our emphasis is on image classification, utilizing the Inception V3 model through transfer learning to classify medical DR images.

Creating a classification model for medical images based on disease type or patient status marks a significant advancement in disease diagnosis. Our study addresses the classification of DR medical chest images into normal and abnormal categories. The incorporation of artificial intelligence (AI) into medical image processing commenced in the 1960s, followed by subsequent research concentrating on the analysis of radiographic images and the identification of abnormal chest radiographs.

In recent years, studies by researchers like Stefan Jaeger, Alexandros Ka Argyris, Mitko Veta, Anton S. Becker, Magda Marcon, and Geert Litjens have explored various aspects of medical image processing, including tuberculosis detection, breast cancer histopathology, and the efficiency of deep learning methods like Convolutional Neural Networks (CNNs) and artificial neural networks (ANNs) in breast cancer detection.

Notably, Junchi Liu and Amin Zarshenas introduced the neural network convolution (NNC) model in 2018 to reduce radiation dosage in breast tomosynthesis.

The remainder of this paper is structured as follows: Section 2 reviews related work on medical images and Inception V3. Section 3 outlines the proposed classifier method. Section 4 details the experiments conducted, and finally, Section 5 provides conclusions and suggests potential avenues for future research.

II. RELATED WORK

Various methods have been proposed to address the classification of medical images, with the application of the Inception V3 model being one such approach. Significantly, we are trailblazers in the application of the Inception V3 model, specifically for the classification of medical images related to Diabetic Retinopathy (DR).

The main goal of this research is to classify medical images related to Diabetic Retinopathy (DR), with a specific focus on distinguishing between normal and abnormal images. A significant distinguishing feature between these two categories is the presence of lung nodules. In a study conducted by Fan Lei, a method was suggested for identifying lung nodules in Computed Tomography (CT) images of the lungs, utilizing 3D Convolutional Neural Networks (CNNs).

The Inception V3 model has previously been employed for the classification of various JPG images for different purposes. As an example, Xiaoling Xia employed the Inception V3 model to categorize flowers, making use of transfer learning technology to retrain datasets specifically designed for flowers.

Several ongoing studies aim to assess the effectiveness of various classifiers for pulmonary diseases, frequently incorporating diverse deep learning principles. One such instance is the investigation carried out by Lakhami and Surdaram, which concentrates on the automated classification of pulmonary tuberculosis using Convolutional Neural Networks (CNNs).

III. PROPOSED METHOD

Numerous diseases affect the chest and lungs, necessitating specialized pulmonologists to analyze radiological images for accurate labeling. Due to a shortage of labeled images, our dataset is classified into two broad categories: normal and abnormal. Convolutional Neural Networks (CNNs) have proven their superiority compared to alternative image classification techniques, showcasing elevated accuracy and proficiency in handling images with multiple layers.

Functioning as a classifier, the Inception V3 model utilizes TensorFlow, Google's second-generation AI learning system. Inception V3, initially developed as a pre-trained model for classifying images into 1000 categories, underwent training on the ImageNet database. Its selection is based on availability and ease of modification, with Inception V3 being the third version following Inception V1 and V2, achieving an error rate of 3.5%.

Transfer learning, a technique in deep learning, utilizes supplementary data from an existing model to augment the understanding of a new image dataset, leading to enhanced outcomes. Ideally, the auxiliary and target data should exhibit common characteristics. Transfer learning offers a significant advantage over CNNs in terms of both time efficiency and accuracy. Figure 1 illustrates the concept of transfer learning, highlighting its additional benefits in terms of time and accuracy.

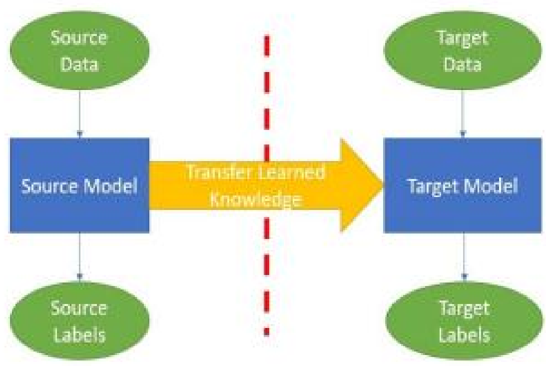


Fig. 1 Concept of Transfer Learnings

A. Transfer Learning

Transfer learning is a machine learning paradigm where a model trained on one task or dataset is adapted and applied to a different but related task or dataset. The primary goal of transfer learning is to leverage knowledge gained from solving one problem and apply it to a new, possibly more complex, problem without starting the learning process from scratch.

B. Inception-v3 Model

The Inception-v3 model is a convolutional neural network (CNN) architecture that was developed by researchers at Google. It is part of the Inception family of models, which are known for their effectiveness in image classification tasks. Inception-v3 represents the third version in the series, following Inception-v1 and Inception-v2 (also known as GoogleNet).

C. Learning Transfer in the Inception-v3 Model

Incorporating transfer learning with the Inception-v3 model entails utilizing a pre-trained Inception-v3 model, typically trained on an extensive and varied dataset such as ImageNet, and customizing it for a particular task or dataset of interest. This approach is particularly beneficial when you have a limited amount of labeled data for your target task, as the pre-trained Inception-v3 model can provide a solid foundation for learning relevant features.

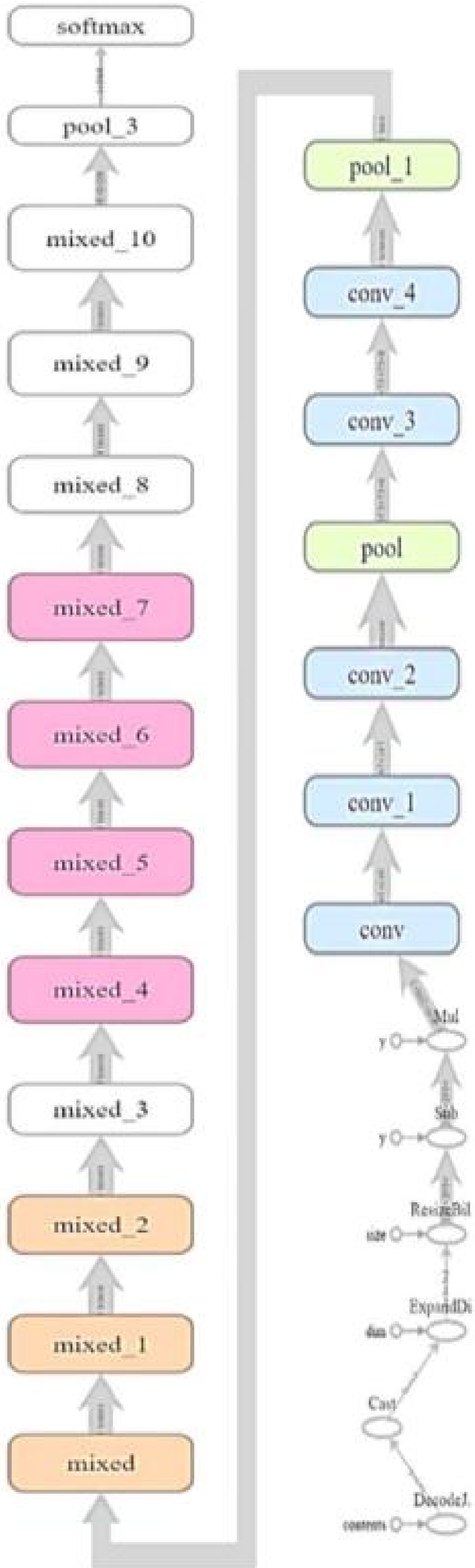


Fig. 2The complete Inception-v3 model graph

IV. EXPERIMENT

To conclude this study, we employed an Intel(R) Core(TM) i5-7400 CPU operating at 3.00 GHz and 4.00 GB of RAM. Our research will be divided into three primary sections: dataset, methodologies, and findings.

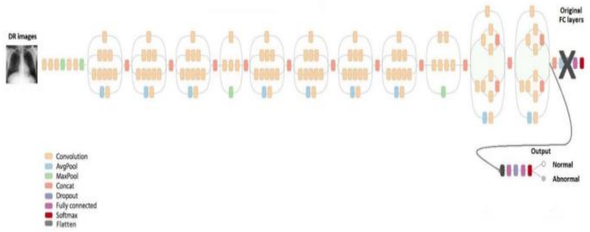
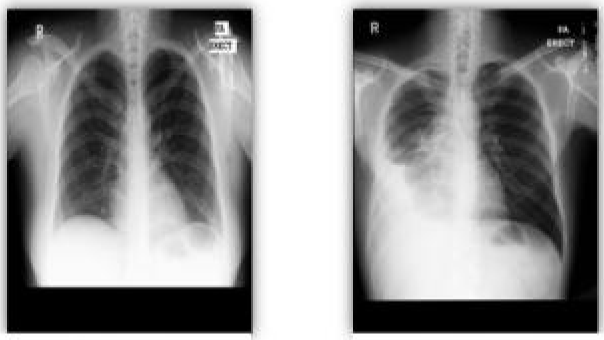


Fig. 3The Inception-v3 customized graph

We divided our dataset into two separate categories: normal and abnormal images. The dataset comprises 80 DR chest images labeled as normal and 57 DR chest images labeled as abnormal. The scarcity of available sources for DR chest images accounts for the relatively limited number. All images in the dataset are in JPEG format.



Normal JPEG Abnormal JPEGA

Fig. 4: An example of a dataset with both normal and Abnormal DR photos

D. Procedure

We divided the DR images into two distinct sets and organized them into separate files to optimize the performance of the Inception V3 model with the dataset. Furthermore, we adjusted the filenames in the dataset by adding a numerical identifier (0 for normal DR chest images and 1 for abnormal DR chest images) to simplify the categorization process. The ultimate layer of our model utilizes the backpropagation method for computing the cost function and adjusting parameters, delineating the delineation of tasks between segmentation and transfer learning.

E. Fragment:

- During this stage, we standardized the size of all images to be uniform.
- Following that, we conducted segmentation to generate binary images, improving the visibility and clarity of lung fields.

F. Inductive Transfer:

- The model utilized parameters such as a learning rate of 0.005, a batch size of 100, and validation/test percentages set at 10% each during network training.
- The model was built upon the weights of the Inception V3 model.
- After the initial training, we refined the network through further training using our proprietary DR images.

V. RESULTS

Tensorboard is utilized to graphically represent the accuracy and cross-entropy graphs for both the training set and the validation set. In Figures 6 and 7, the orange line corresponds to the training set, while the blue line corresponds to the validation set.

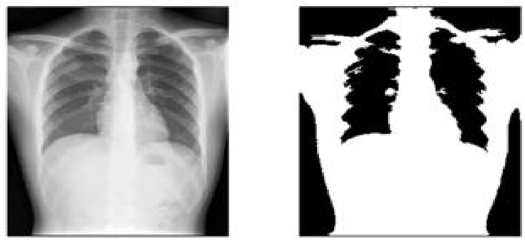


Fig. 5. Image processing

G. Accuracy

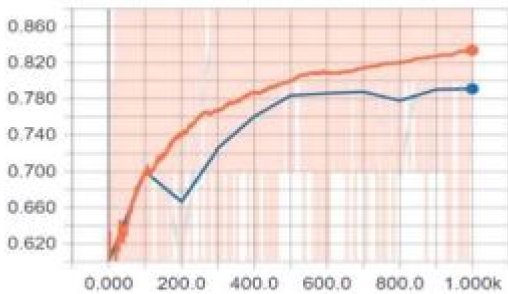


Fig. 6. Accuracy values for the validation set and the training set.

H. Cross_Entropy

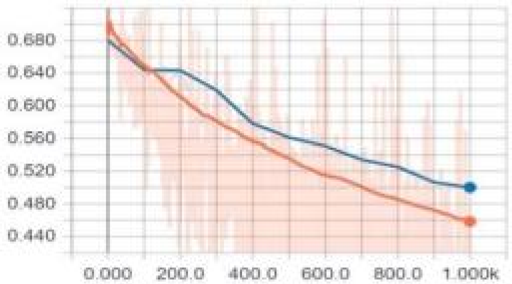


Fig. 7. Values of cross-entropy for the training and validation sets.

The training dataset consistently demonstrates elevated values compared to the validation dataset, as anticipated given that the validation set comprises only 10% of the entire dataset. The point of convergence between the training and validation sets occurs approximately at 200 steps. Likewise, the training set surpasses the performance of the validation set, and the point of intersection between the two occurs at around 100 steps.

TABLE I
INDEX AND PERFORMANCE

Index	Performance
The training set accuracy	83.37%.
Validation set accuracy	79.12%
Training set cross-entropy	0.45749
Validation set cross-entropy	0.5004

VI. CONCLUSIONS

In this study, we utilized the Inception V3 model and adopted a transfer learning approach to enable the classification of DR images into two categories: normal and abnormal. The model achieved an accuracy of 83.3% in this classification task. Our future efforts will focus on improving this model by incorporating additional DR images and expanding the labeled dataset.

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